Environmental Energy Technologies Division

Building Energy Models Can Be Automatically Adjusted To Fit Data

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Project Overview

- Performance of building energy models could be improved.
- Currently building energy models are created using assumptions of HVAC equipment and building material parameters and generic occupancy and load patterns.
- Tuning models, especially those that are highly resolved, can be extremely time-consuming.
- Building energy model capabilities, availability of actual building energy end-use data, and computing power are increasing.
- Above led us to think why not use actual building data and innovative optimization methods to improve the performance of building energy models.

Project Acknowledgements

- Building energy model
  - *Doug Black, Pam Berkeley, and Amanda Webb*
- Optimization software
  - *Phil Price and Nathan Addy*
  - GenOpt technical guidance by *Michael Wetter*
- Computing resources
  - *Noel Keen (CRD)*
- Building data
  - *Mike Spears, Mike Apte, and John Elliott (UCM)*

Project Goals

- Make it feasible for researchers to investigate the reasons design models, in some cases, fail to make good predictions to:
  - Improve modeling software;
  - Learn which parameters are most important.

- Make it feasible to routinely make reasonably accurate models of existing buildings to:
  - Predict energy savings from retrofits or changes in operation;
  - Enable "model-based controls and optimization";
  - Enable automated fault detection and diagnosis.

UC Merced Building Classroom and Office Building

- 92,000 ft^2 (8500 m^2)
- 30 classrooms, 100 offices, auditorium, open office area
- Sub-meters for lighting, plug-loads, HVAC fans, CHW, HW
- High-quality historical data

EnergyPlus Model of COB

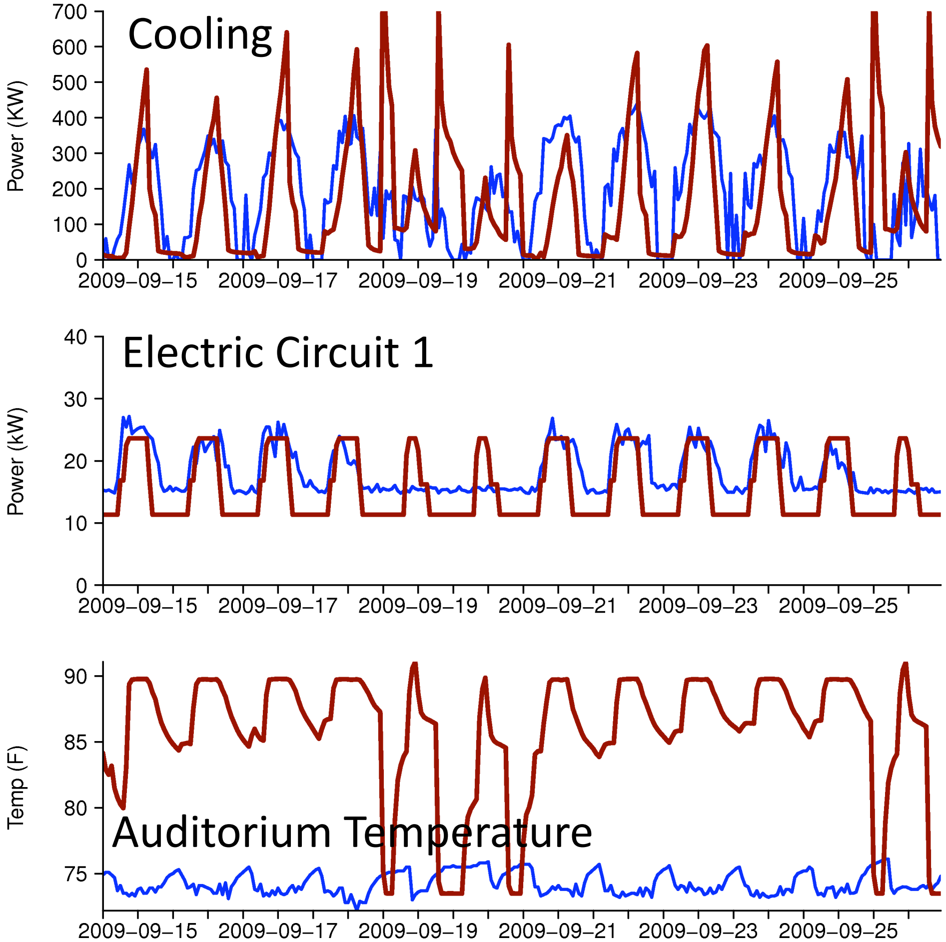
- Chose Energy Plus because it is the state of the art building energy simulation tool with widest range of capabilities.
- Model was also used for study of occupancy based controls, which required high spatial resolution (86 conditioned zones).
  - Building surfaces (771); Day Schedules (1094)
- Optimization project has spanned 3 versions of EnergyPlus.
  - Dual fan dual duct; model has a single cooling fan and actual building has two cooling fans
  - Relief fan control implemented with EMS script

General Optimization Approach

- Select model outputs to use in a performance metric.
  - Depends largely on available building data
  - Can depend on model's purpose (energy, comfort, etc.)
- Performance metric is basically the sum of the differences between predictions and measurements.
- Select model parameters that will be adjusted and the ranges over which the parameter values can vary.
- Run multiple models in parameter "space" to find model with best performance metric score.

Model Optimization

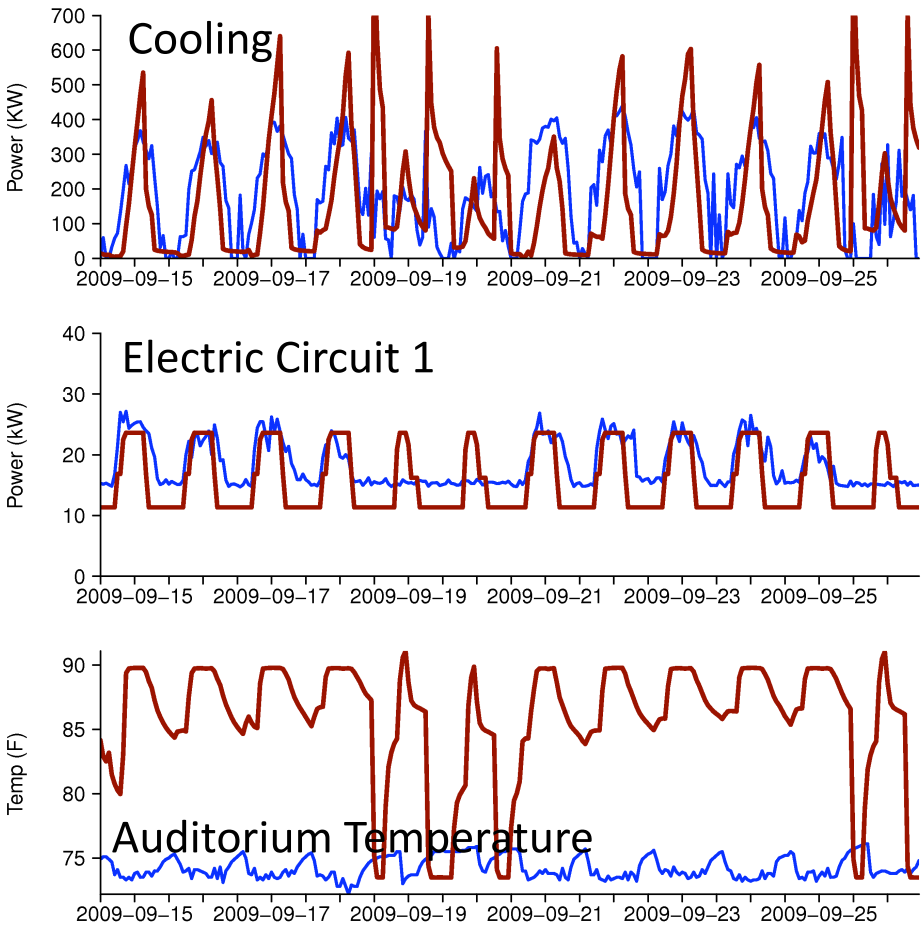
Model with initial parameters



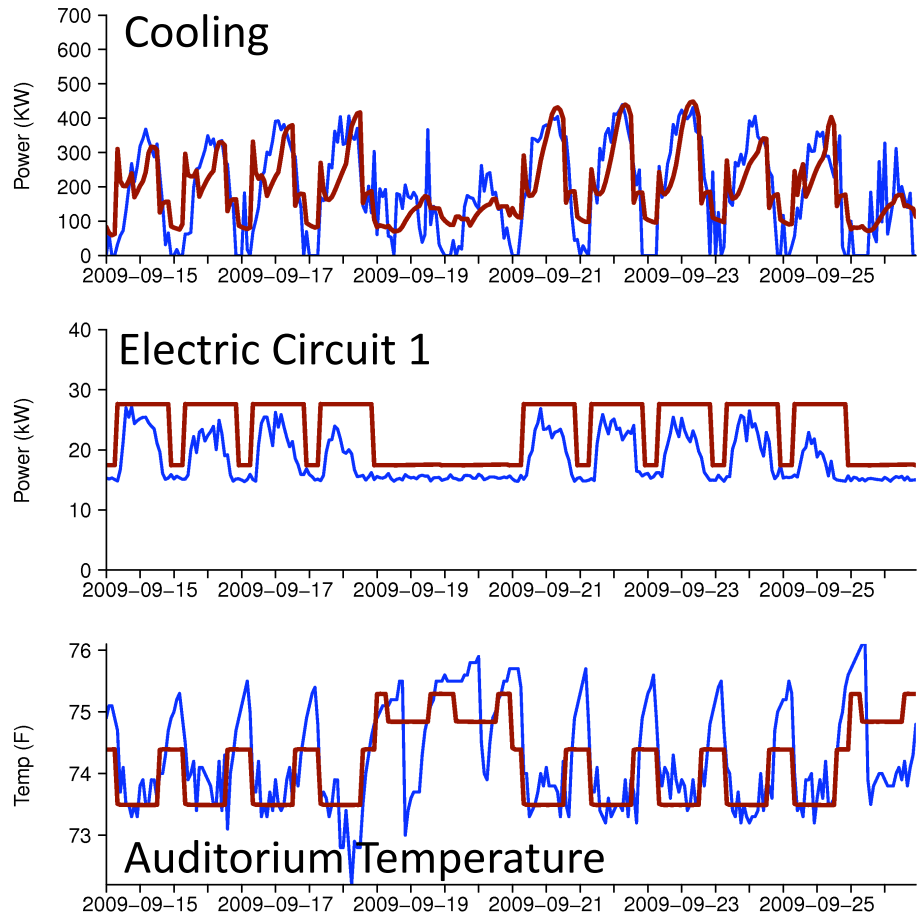
Blue = data, Red = prediction

Automated Optimization for a 2-Week Period

Model with initial parameters



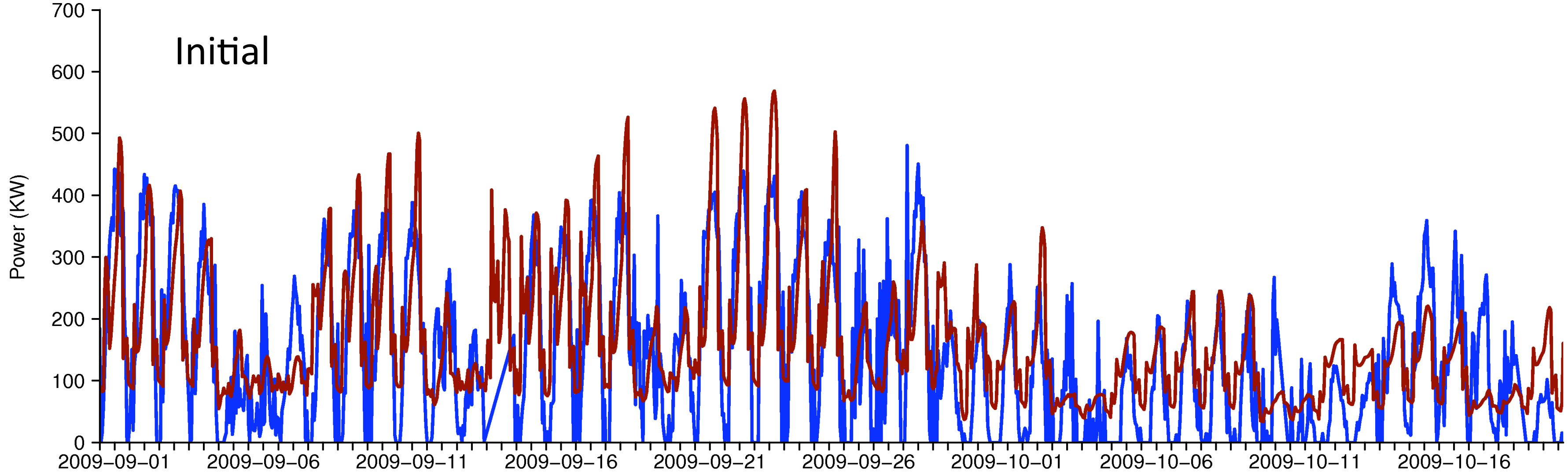
Optimized model fits better



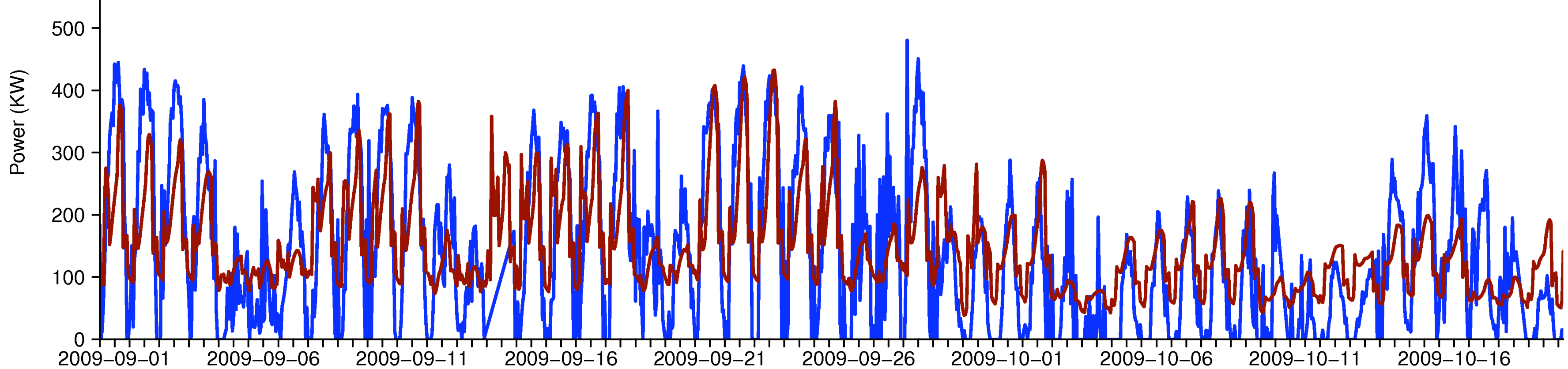
note: y-scale differ

Blue = data, Red = prediction

Automated Optimization for a 2-Month Period Cooling Energy

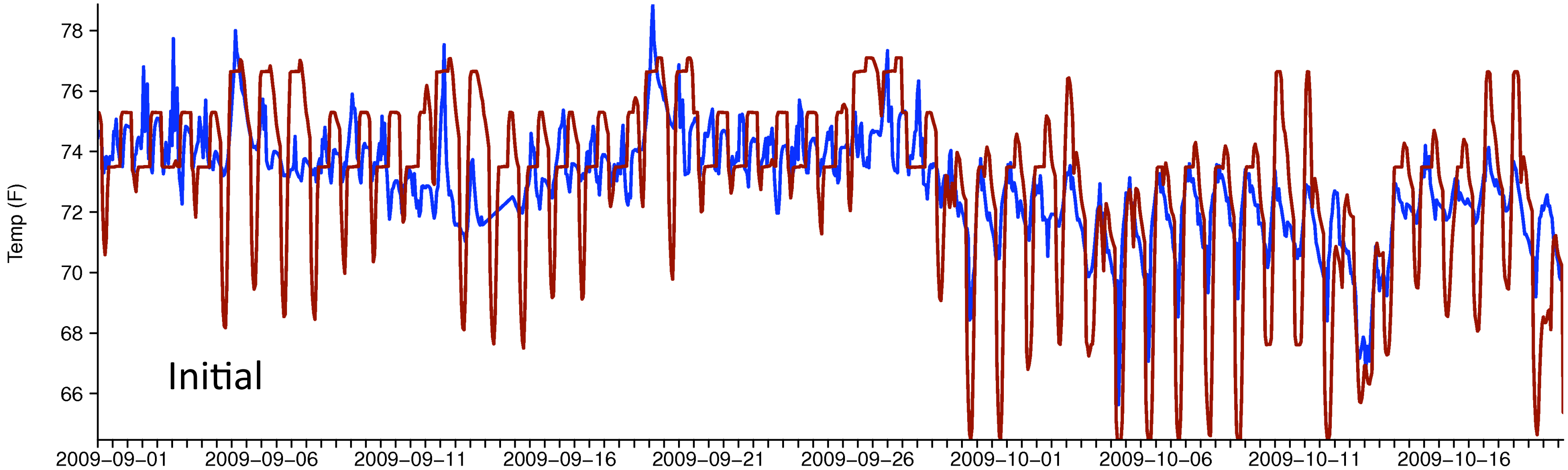


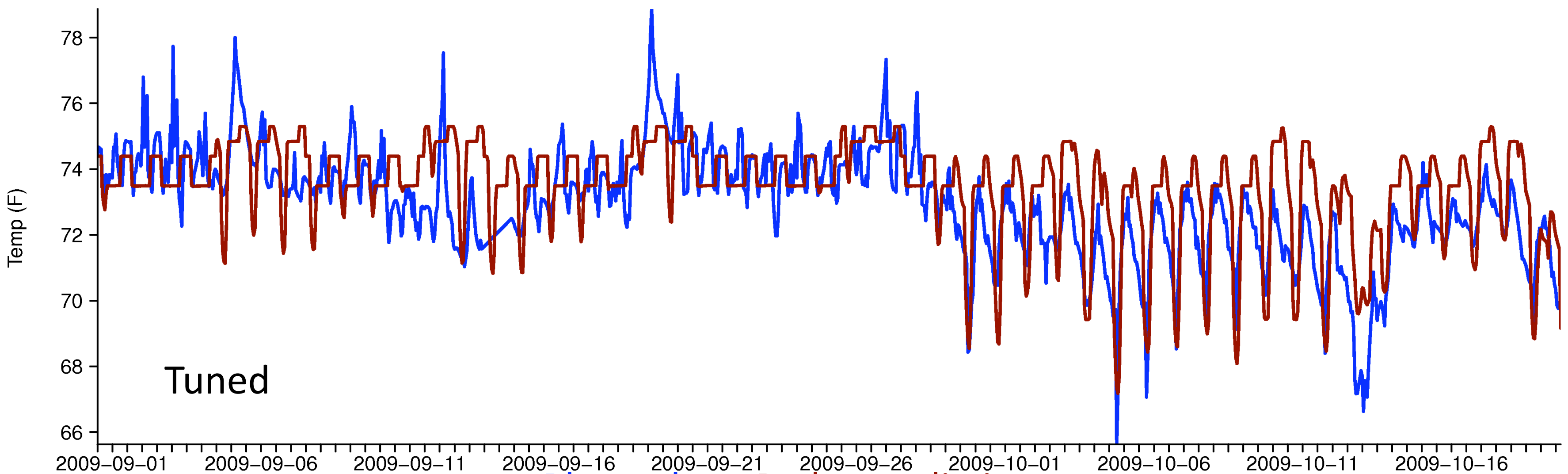
Using a longer time interval reduces the risk of "over-fitting," but (unreported) building operations may have changed.



Blue = data, Red = prediction

Automated Optimization for a 2-Month Period 1st Floor Corridor Temperature





Blue = data, Red = prediction

Optimizing an Energy Plus Model

- Framework for optimization
- Parameterization Strategies
- Optimization Algorithms

Optimizing an Energy Plus Model - Problem

We start with an Energy Plus model and data from the real building.

Someone says "Optimize it".

What happens next?

Optimization Framework – Define an Objective Function

We can numerically minimize functions

Make a function that takes model parameters and returns a measure of the error in the corresponding model.

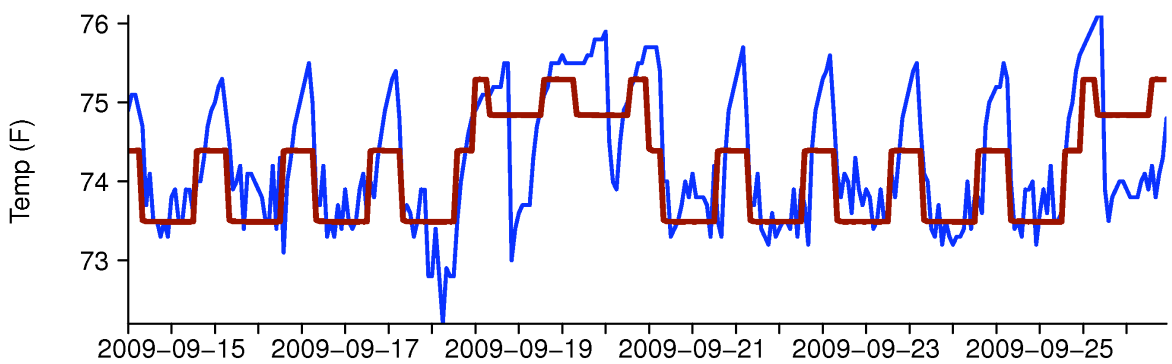
Minimize that function.

Defining our Objective Function

Sensor data

- cooling and heating power
- circuit power
- zone temperatures
- fan power

Compare real data to predicted using RMS error



Convert to equivalent units

Other software requirements

We need to be able to handle "real-world" sensor data.

- Missing sensor data
- Sensor data coming in at unusual/misaligned intervals
- Sensor data not in the form we need it to be
- Same for model output

STEM (Software for Tuning Energy Models) does this

Our Objective Function

RMS cooling power error

+

RMS heating power error,

+

RMS circuit power errors (4 of them),

+

RMS fan power errors

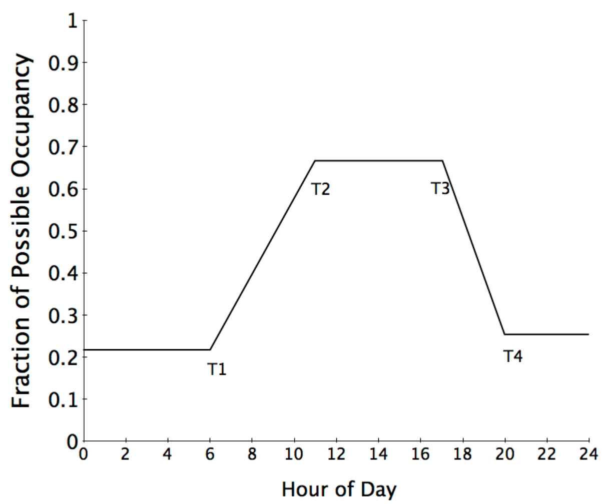
+

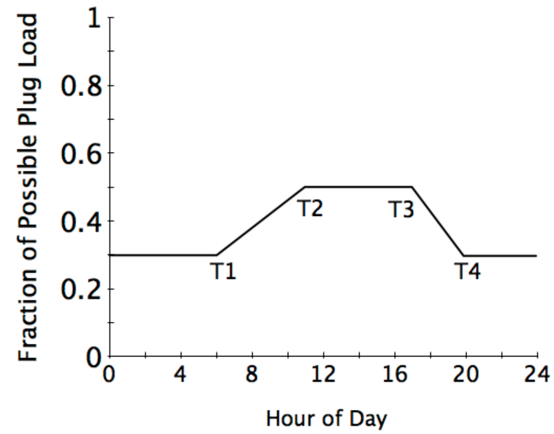
81 temperature RMS errors (all converted to "equivalent" energy units).

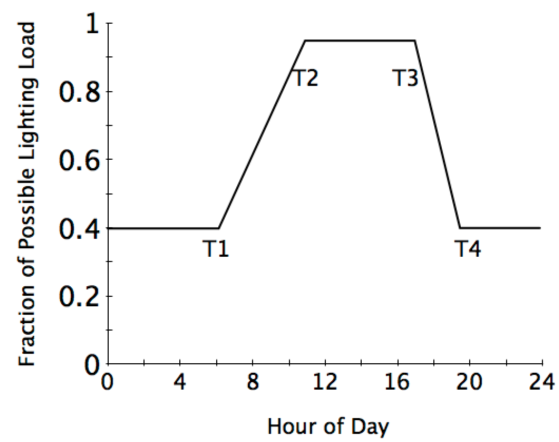
Parametrizing a Building Model

Oftentimes, the parameters we wish to optimize are not found directly in the model

Example: Schedules







Parametrizing our Model

Two classes of optimization

1) 12 parameters

2) 56 parameters,

Half are "indirect" parameters.

Other Preprocessing

We can add observed data into the model
- Circuit power using plug load schedules
- Temperatures using setpoint schedules

We can use other software tools to help set up parameterizations.
- Clustering zones by estimated temperature setpoints

Optimization Methods

Hooke-Jeeves

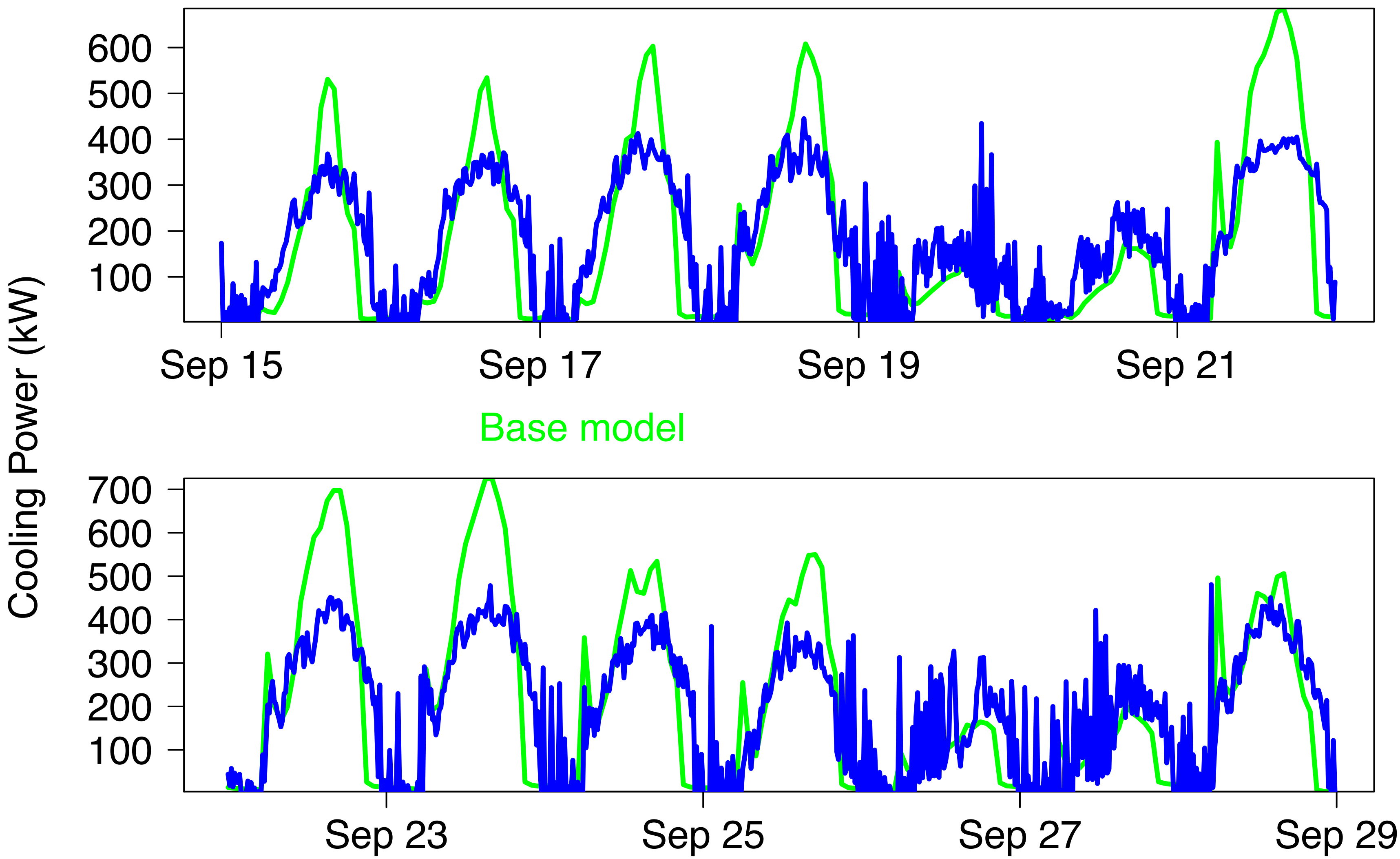
- "Intelligent" optimization.
- Implemented via GenOpt
- Suitable for single-processor machines.
- 1 week on a desktop machine.

Particle Swarm Optimization

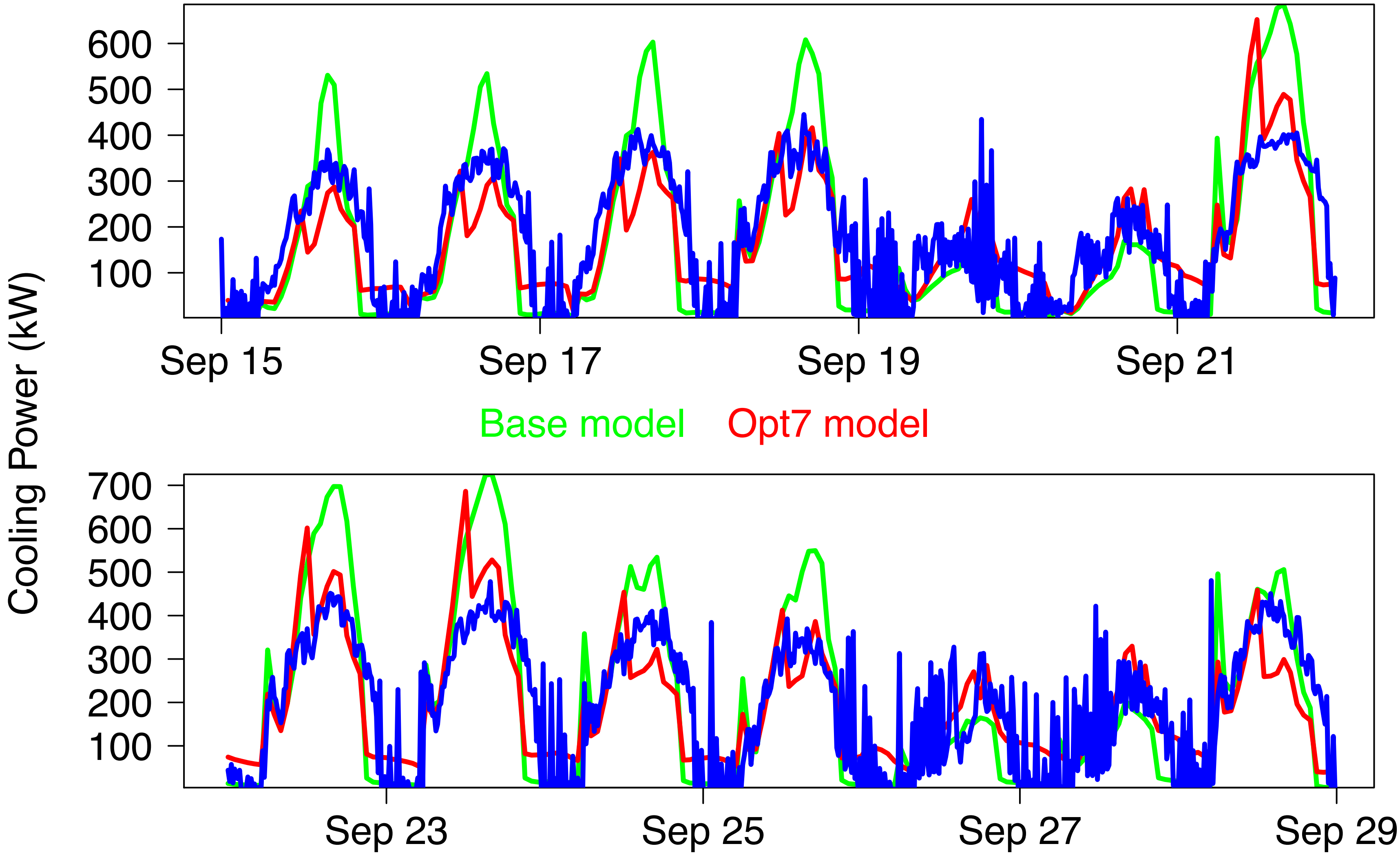
- Imagine a school of fish looking for "hot-spots".
- Suitable for running on a cluster or the cloud.
- < 24 hours on NERSC computers; < 4 for small problems

Many others available

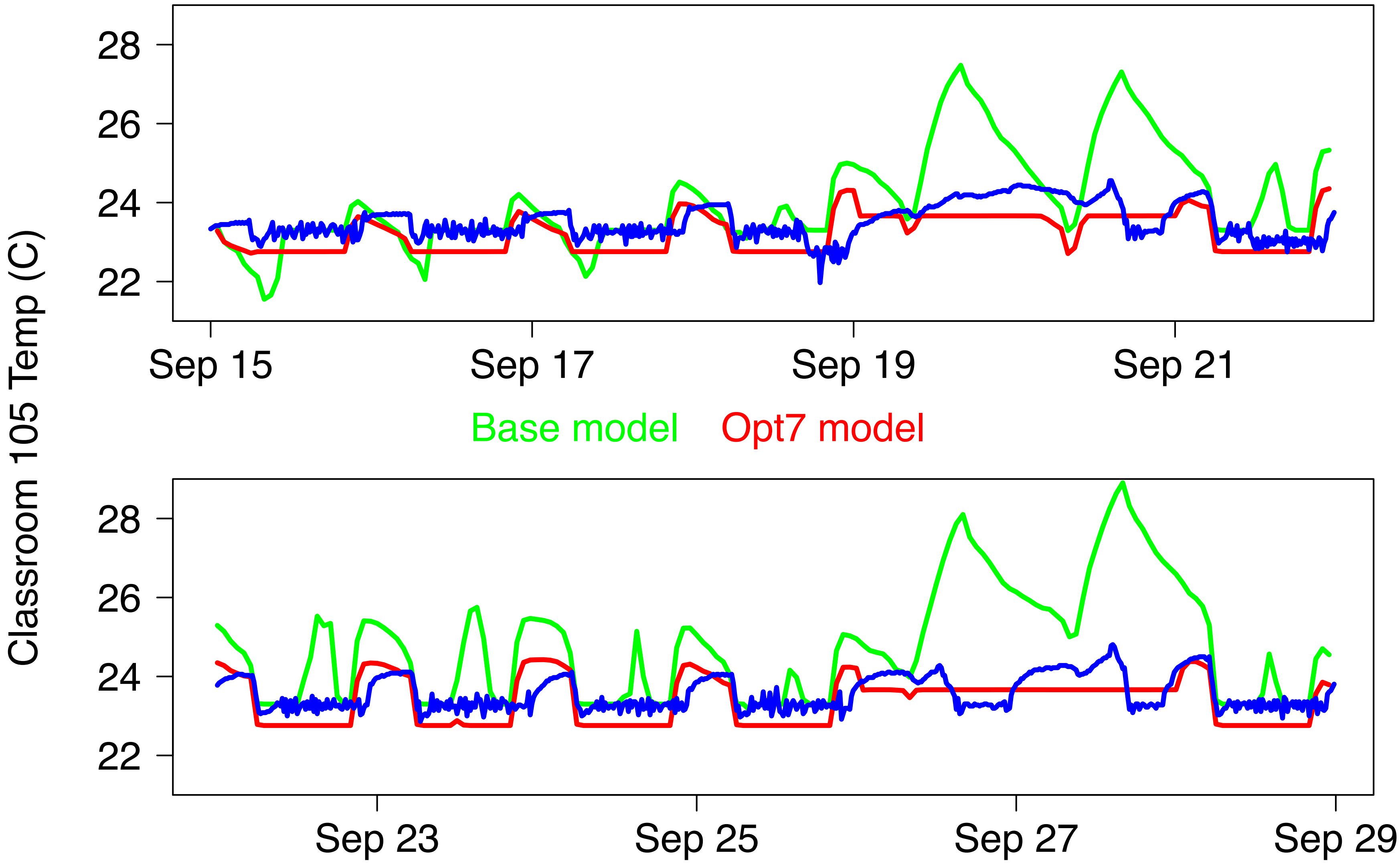
Hand-tuned "Base" model has RMS error of 78 kW in cooling power



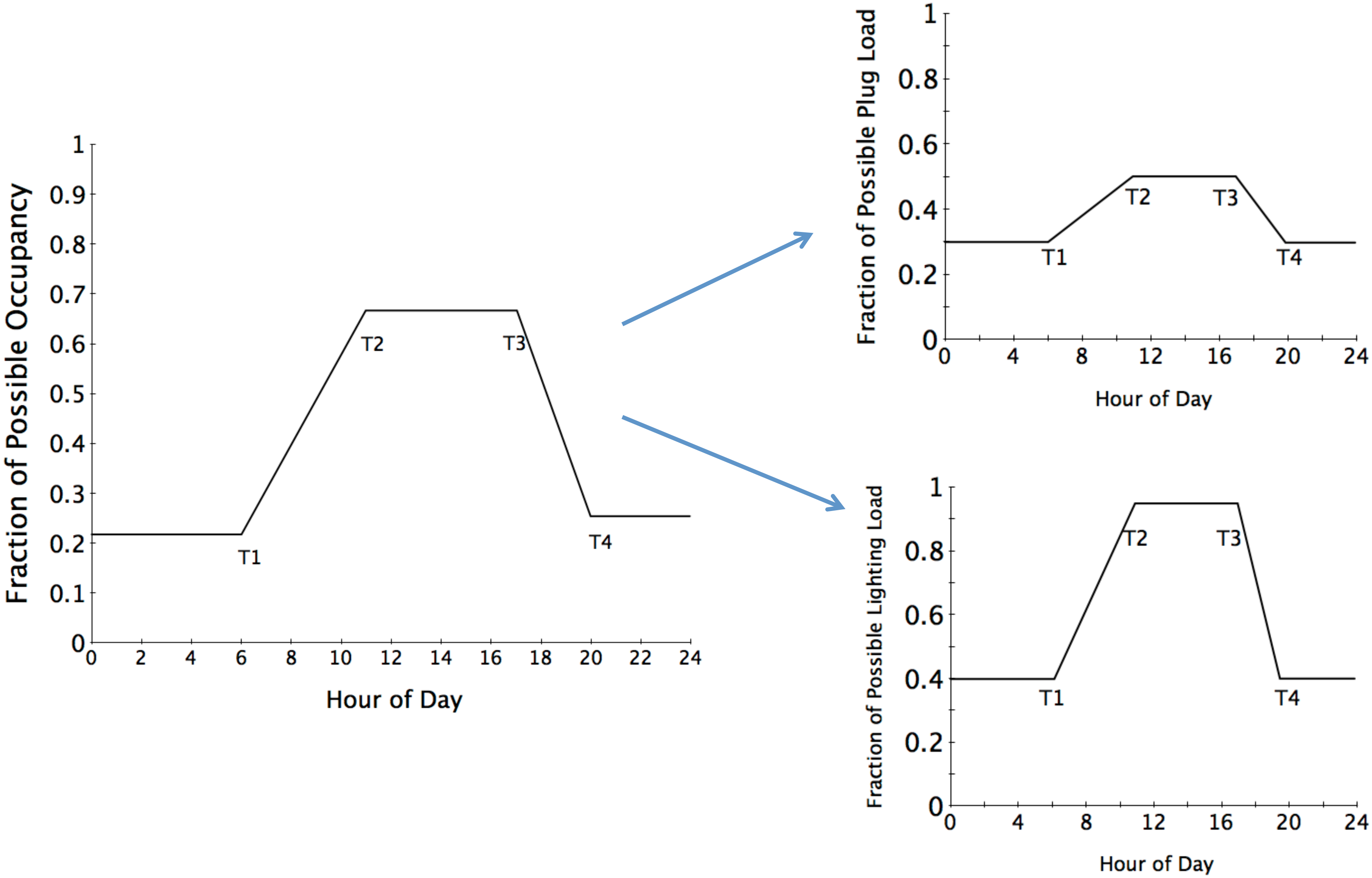
Model "Opt7" has RMS error of 73 kW in cooling power; only 8% lower error than Base Model



But classroom temperatures are better in Opt7 than in Base (RMS error is reduced 40%)



We assume there is an underlying "occupancy schedule" that determines plug load and lighting schedules



Opt7 has lots of parameters, and could use more!

Opt7 optimizes about 60 parameters

6 parameters describe classroom weekday occupancy schedules; all classrooms are assumed the same, and every weekday is assumed the same.

6 describe classroom weekday schedules

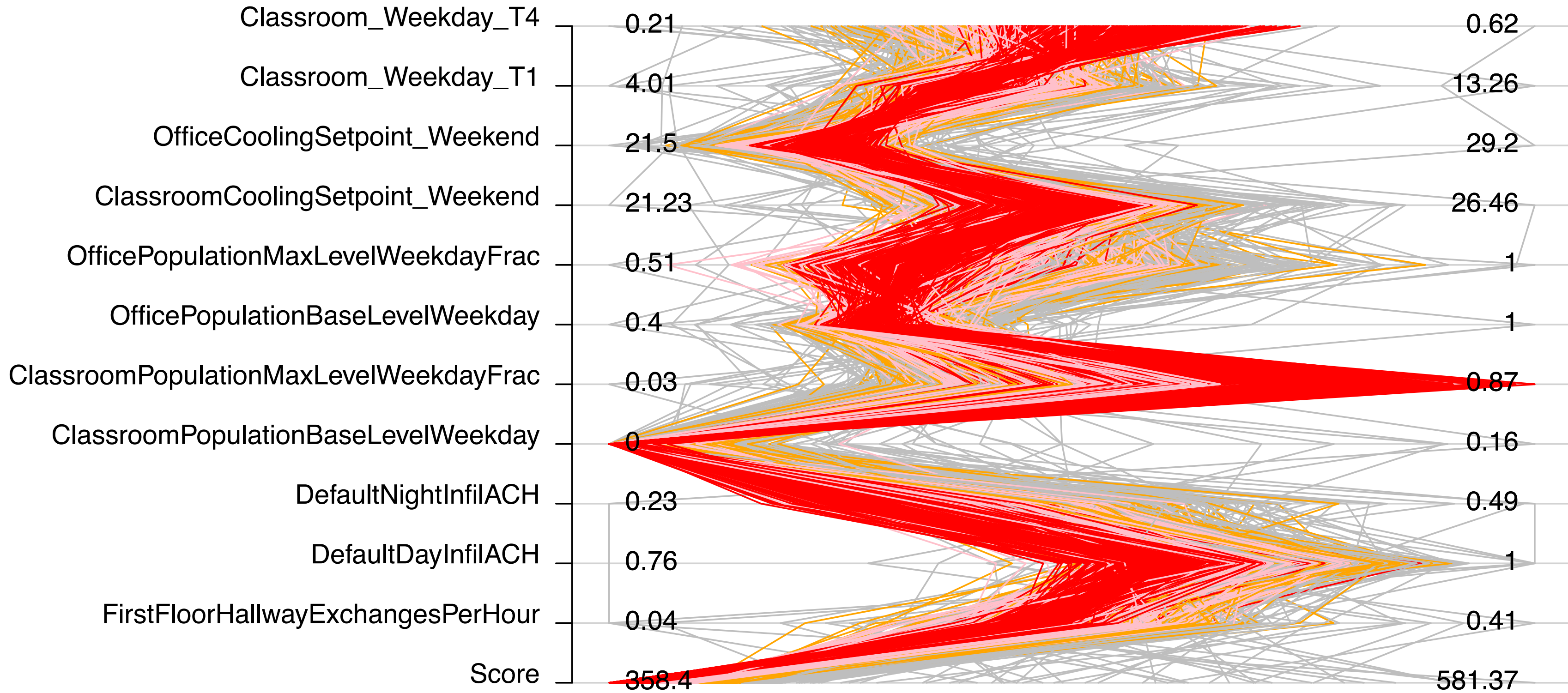
6 describe office weekday schedules

6 describe office weekend schedules

Other parameters include air infiltration into perimeter zones (night and day); base and maximum plug loads; and many more.

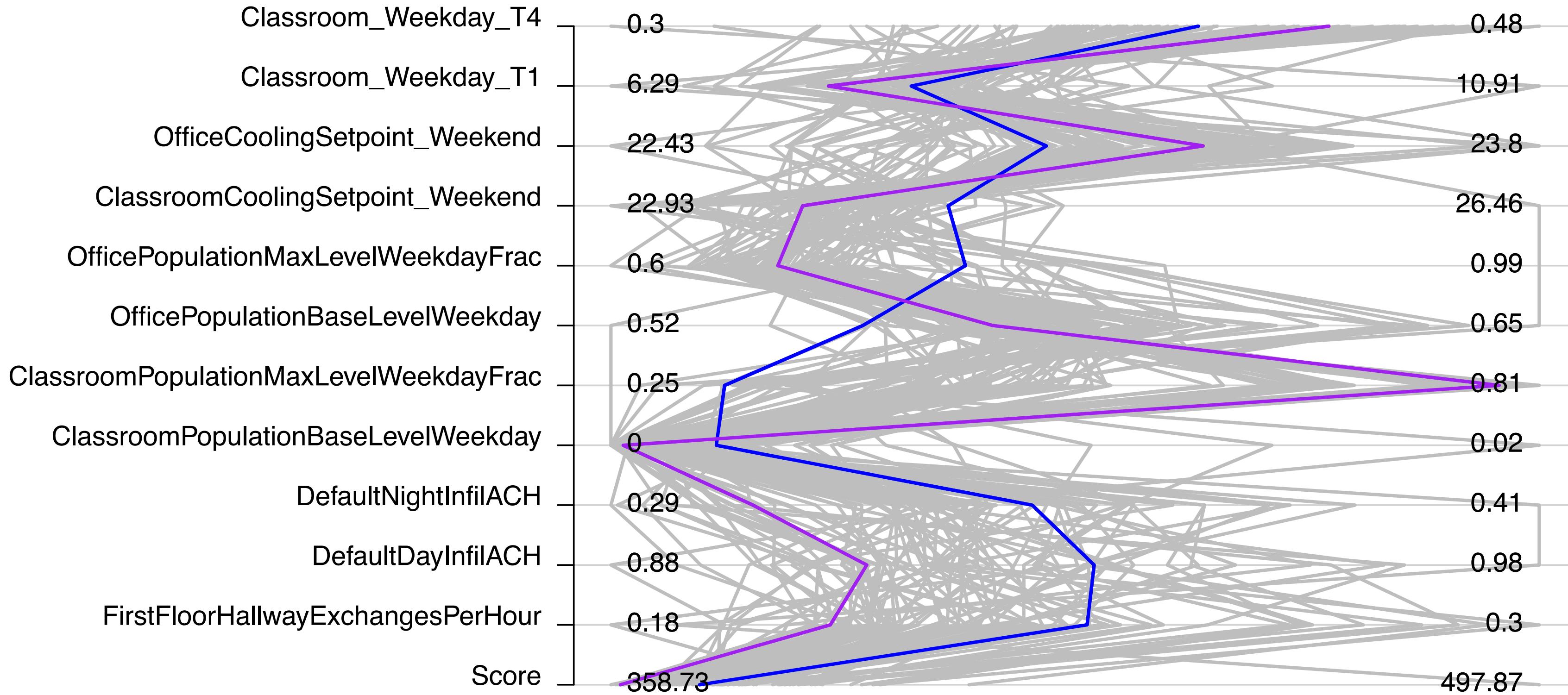
We can optimize this for a three-month simulation in a few hours.
Thanks, NERSC! Thanks, Noel Keen!

Some Opt7 parameters are tightly constrained; others aren't.

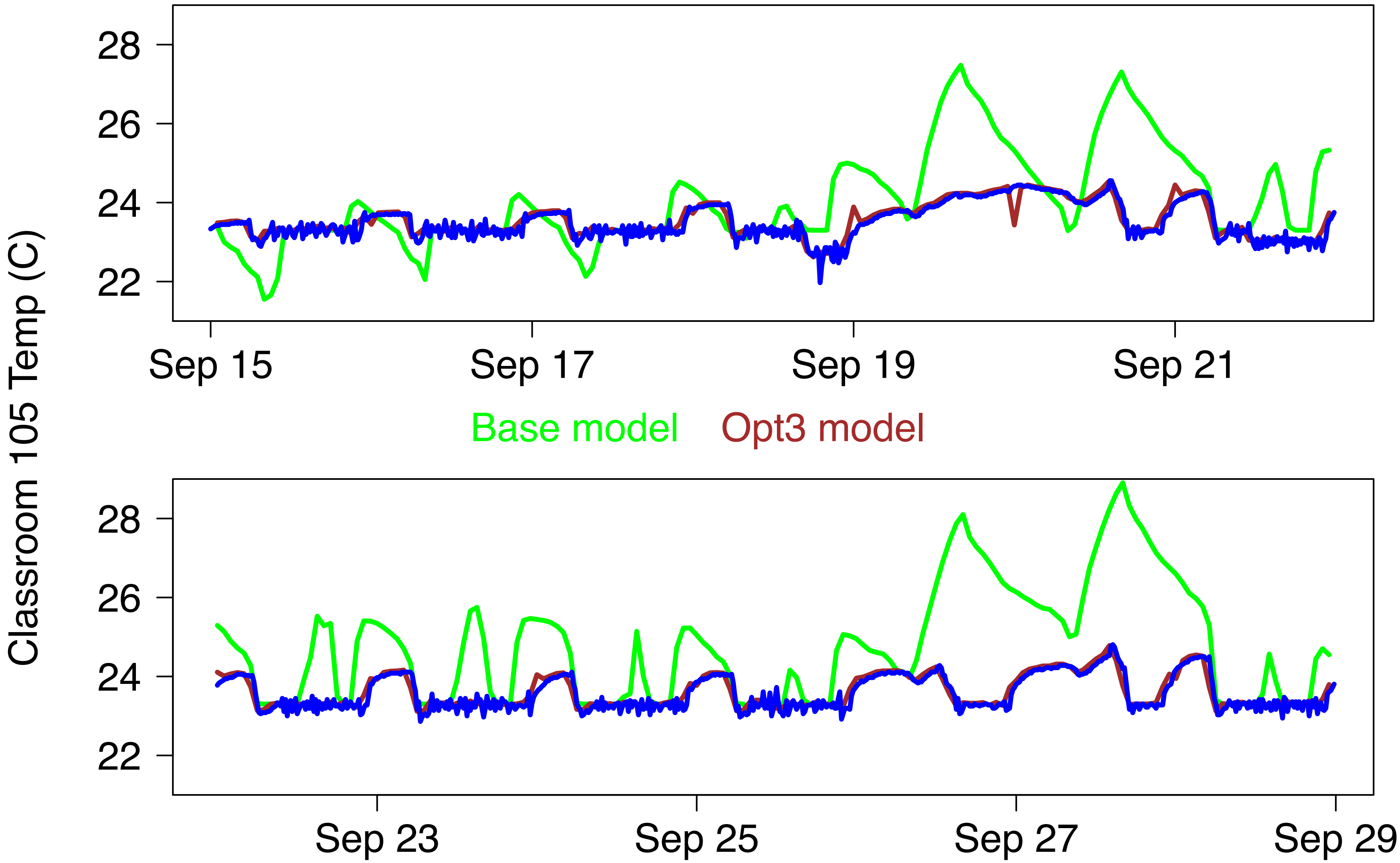


"Parallel coordinates" plot is a good way to display many parameters. "VisIt" is a nice platform for this. (Thanks Prabhat of Computational Research Div.)

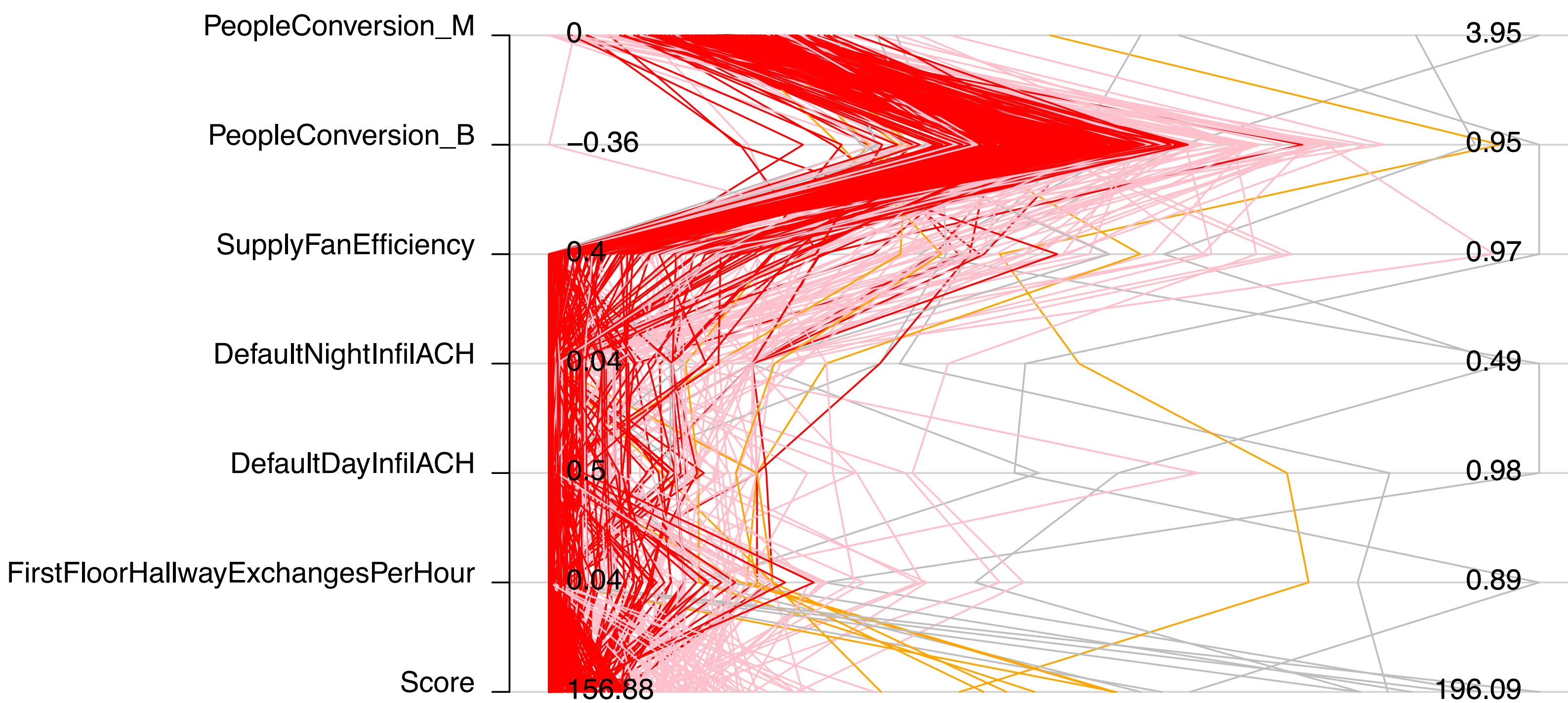
Similar scores, different parameter values



We can also impose temperatures with schedules for every day, for every zone, using HVAC schedules



A model can fit well with bad parameter values



Opt3 has essentially no temperature error. The cooling error is about the same as Opt7 and is slightly better than the base model. Overall the fit is much better than the base model. But these fan efficiency and hallway infiltration values can't be right.

Should energy models be automatically adjusted to fit data?

Just because you *can* do it doesn't mean it's a good idea.

Everybody who builds an energy model of a real building adjusts it to fit data. Software will do this much faster than hand-tuning. ***Good!***

Automated fitting ensures that you can find the best fit. ***Good!***

If even the best fit isn't good, you've learned something important. ***Good!***

Optimized parameters can give you clues about ways in which your model is structurally deficient; for instance, if some parameters "want" unreasonable values, they're telling you something. ***Good!***

Particle swarm (or other approaches not yet implemented) can help evaluate sensitivity: can tell which parameters, if any, can be pinned down by the data ***Good!***

Should energy models be automatically adjusted to fit data?

There is a tendency to keep blindly fitting slightly altered models in the hope of striking gold. ***Bad!***

There is a tendency to think that if the model fits well, its parameters must describe the real building. ***VERY bad (if you succumb to this tendency)!***

CONCLUSIONS

Adjust your model to fit data
Use our STEM software to do it (you will need our help)
Look at the model parameters: do they make sense? Are they telling you something?
Adjust the model if necessary, then re-fit
Don't focus just on the fit metric: the model that fits best is not the best model!